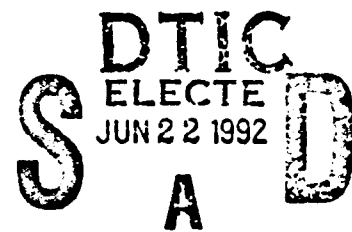


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Final Report

**DENSE MODIFIABLE INTERCONNECTIONS  
UTILIZING  
PHOTOREFRACTIVE VOLUME HOLOGRAMS**

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19. ABSTRACT (Continue on reverse if necessary and identify by block number) This report summarizes research efforts on (1) the demonstration of holographic degeneracies in associative memories, (2) the procedure for designing fractal grids for planar holograms, (3) the experimental demonstration of one and two layer neural networks that are designed with such fractal sampling grids, (4) the experimental demonstration of dynamic holographic memories that are capable of an arbitrarily long sequence of adaptations, (5) the optical implementation of the Kanerva's network for hand-written character recognition, (6) the development of an anti-Hebbian local learning algorithm for training multi-layer neural networks, (7) the experimental demonstration of optical radial basis function network, and (8) the demonstration of a two-layer local-representation optical network for real-time face recognition.			
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This is the final report for the AFOSR sponsored program "Dense Modifiable Interconnections Utilizing Photorefractive Volume Holograms" (AFOSR-89-0045). Here we present an overview of the accomplishments which have been described in more detail in the semi-annual reports as well as the published papers that are listed at the end of this report.

The basic architecture for holographic optical neural networks [1,2] is shown in Fig. 1, which can be a single stage of a multilayered system. Neurons in one plane are interconnected with the neurons in other planes via holographic gratings stored in light sensitive media such as photorefractive crystals. Specifically, the light from a pixel at the input neural plane is collimated and diffracted by a holographic grating. The diffracted light is then focused by a lens onto a pixel at the output neural plane. The goal is to train such a system, through modifications of the holographic interconnections, in order for it to perform desirable computations. The success of this learning procedure depends critically upon the optical hardware and the learning algorithm. It has been the objective of this research program to realize dense modifiable interconnections in such adaptive systems using photorefractive volume holograms.

A basic geometrical limitation on the density of interconnections achievable through volume holograms is due to the finite volume of photorefractive crystals. Let  $N$  be the number of resolvable points in any one dimension for both the neural planes and the hologram. There are  $N^2$  pixels in both the input and output planes. On the other hand, the total number of gratings available in the hologram is  $N^3$ . Therefore, if we want to interconnect independently each of the input neurons to all the output neurons, only  $N^{3/2}$  pixels from the  $N^2$  available sites at each plane can be selected for the placement of neurons. The sampling procedure [3,4] is described as follows. Each time we attempt to add a neuron to a new site at the input (output), we check to see whether this new site is already connected to one of the neurons selected previously at the output (input) by an existing grating. If it is, we eliminate this site from the sampling grid; if it is not, we place a neuron at this site, which implies that gratings are established to connect this new neuron to all the neurons now selected at the output (input). By iterating this procedure, we can find sets of fractal sampling grids that must be used in the input and output planes so as to guarantee that all the interconnections between the input and output planes

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can be independently specified. A large family of sampling grids were derived using this procedure.

To solve a practically significant problem, neural-net learning algorithms typically require at least thousands of iterations (or, modifications of synaptic interconnections). In the optical implementation shown in Fig. 1, each iteration requires an additional holographic exposure to be made in the same crystal. Therefore, a very large number of holograms must be superimposed in a learning architecture. The basic problem with writing a large number of photorefractive holograms is that during the exposure of new holograms, previously recorded holograms decay due to a photogenerated increase in the free carrier density. As a result, the overall diffraction efficiency becomes inversely proportional to the number of holographic exposures [5]. This rapid decrease of diffraction efficiency severely limits the extent to which optical neural networks can be trained. One method to overcome this problem is dynamic copying [6]. The basic idea is to transfer the multiply exposed hologram to a second medium, and then copy it back with a single exposure to rejuvenate the primary hologram. As a result, the overall diffraction efficiency after copying becomes independent of the number of holographic exposures used to form the original hologram. Several variations of this method have been demonstrated, including copying with with an all-optical feedback loop [7], with a pair of active phase conjugate mirrors [8], between two photorefractive media, and with an optoelectronic feedback loop. These methods allow us to construct optical learning networks capable of an arbitrarily long sequence of adaptations.

The types of learning that can be implemented on an optical network fall into two broad categories depending on the characteristics of the hidden layer representation: learning with distributed representation and learning with local representation. In the distributed learning, the network is trained so that a large fraction of hidden units is turned on for each input, while for learning with local representation, only one or a small number of hidden units are turned on for each input.

Examples of distributed learning networks include Kanerva's network [9], the Back-propagation network [10], the ALL network [11,12], and the tiling network. In the Kanerva's network, the weights of the first layer interconnections are random, and each input is mapped to a sparse, distributed hidden representation. The second layer, trained by

the sum-of-outer-products rule, perform classification on the distributed hidden representation. Figure 2 shows the optical implementation of the Kanerva's network, which was constructed and trained for hand-written character recognition. After training with 104 patterns, all the training patterns were recognized correctly by the system. Figure 3 shows some examples of the input patterns, their distributed hidden representations, the responses of the output units. The position of the switched-on output units indicated which character in the alphabet is the input. The trained network was also tested with 520 handwritten character patterns (20 patterns from each class) that were not in the training set. 311 out of the 520 testing patterns were correctly classified, giving an average recognition rate of about 60%. This recognition rate is much better than random guessing (4%), but far below what is required for a useful character recognition system. The reason for the relatively poor performance on the test set is the choice of training algorithm used, specifically the fixed first layer weights and the limited number of training cycles for the second layer. This same system can be used to implement algorithms in which both layers are fully trained with error driven algorithms such as Backpropagation and ALL, which, in computer simulations, give much better performance.

Learning in both the Backpropagation network and the ALL network aims at reducing the output error at each iteration. While the former requires that the output error be propagated backwards through the network, the latter does not. Although this advantage comes at a price of relatively slow learning rate, the simplicity of the ALL network makes it very attractive for optical implementation in the near future. Both the Backpropagation and ALL networks maintain a fixed size during the training and only the interconnections are modified. The tiling network, however, does not have a fixed size. Rather, it grows during training. Specifically, the network starts with a single hidden unit that is trained with the perceptron algorithm, and more hidden units are added only when they are needed. Compared with local learning, distributed learning can generally yield small networks that can generalize well from a relatively small set of examples. However, these networks are very difficult to train.

Local representation networks are relatively easy to train, but they usually require a relatively large size and large number of training samples. A typical example is the Radial Basis Function (RBF) network. The first layer of the network is trained to generate an

array of basis function centers. When an input is given, the network will calculate the distance between the input and the centers, and a hidden unit will be turned on when the input is close to the corresponding center. The output response is a weighted sum of the hidden layer response. Optical RBF networks have been constructed using optical memory disks [13] and spatial multiplexing parallel architecture [14], and have been successfully trained for hand written character recognition.

Recently, a two-layer local-representation optical network has been constructed and trained to recognize in real time "Denk", who is a student in our group. The network is implemented with liquid crystal spatial light modulators for the neural planes and lithium niobate photorefractive crystals for the interconnections. The network has approximately 60,000 units at the input plane, 30 hidden units, and a single output unit. The output unit is turned on whenever the network classifies the input as Denk. The network is trained with a video segment 2 minutes long, from which 180 frames were selected for training. Specifically, each hidden unit was trained to respond to 6 frames. The trained network classified the rest of the training tape almost flawlessly. The system was then tested by presenting through a TV camera real time input of Denk and other members of our group. The system almost never misclassified other people as Denk and exhibited remarkable tolerance to changes in aspect, illumination, and facial expression.

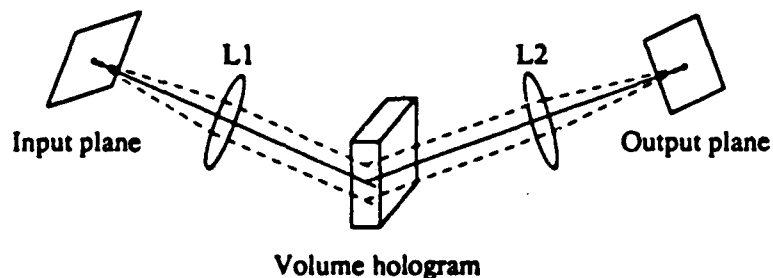


Figure 1. Basic architecture for holographic optical neural networks.

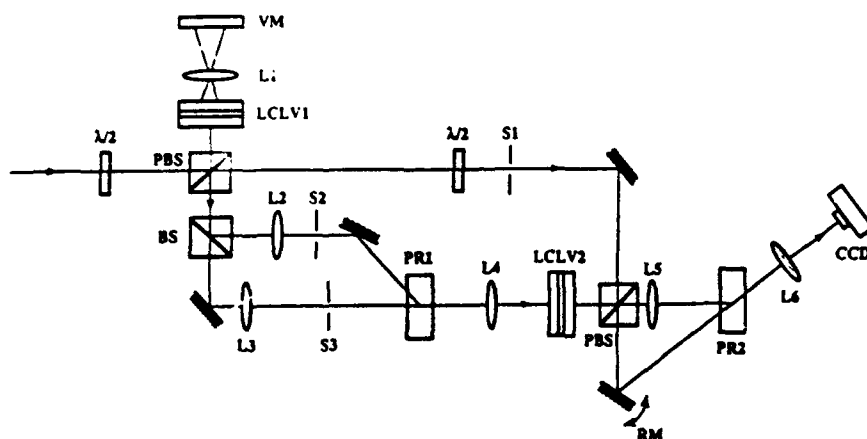


Figure 2. Optical implementation of the Kanerva's network. VM = video monitor, LCLV = liquid crystal light valve, PR = photorefractive crystal, (P)BS = (polarizing) beam splitter, RM = rotating mirror, L = lens, S = shutter.

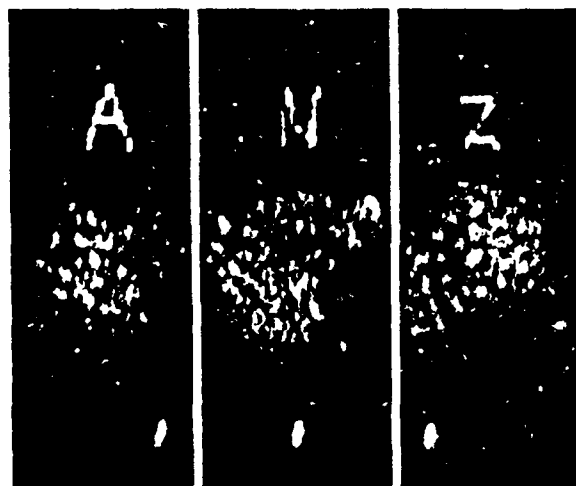


Figure 3. Examples of the signals at the input (top), hidden (middle), and output (bottom) layers in the experimental two-layer network.

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Claire Gu (now an assistant professor at Pennsylvania State University)

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Mark A. Neifeld (now an assistant professor at University of Arizona)

Alan Yamamura (now with Goldman-Sachs Company)

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